Measuring the Stringency of Land-Use Regulation: The Case of China's Building-Height Limits

Brueckner, Jan and Fu, Shihe and Gu, Yizhen and Zhang, Junfu

UC Irvine, Southwestern University of Finance and Economics, Jinan University, Clark University

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Jan K. Brueckner, Shihe Fu, Yizhen Gu and Junfu Zhang*

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Abstract

This paper develops a new approach for measuring the stringency of a major form of land-use regulation, building-height restrictions, and it applies the method to an extraordinary dataset of land-lease transactions from China. Our theory shows that the elasticity of land price with respect to the floor-area ratio (FAR), an indicator of the allowed building height for the parcel, is a measure of the regulation's stringency (the extent to which FAR is kept below the free-market level). Using a national sample, estimation that allows this elasticity to be city-specific shows substantial variation in the stringency of FAR regulation across Chinese cities, and additional evidence suggests that stringency depends on certain city characteristics in a predictable fashion. Single-city estimation for the large Beijing subsample, where site characteristics can be added to the regression, indicates that the stringency of FAR regulation varies with certain site characteristics, again in a predictable way (being high near the Tiananmen historical sites). Further results using a different dataset show that FAR limits in Beijing are adjusted in response to demand forces created by new subway stops.

Keywords: Floor-area ratio, density restriction, urban development, China.

JEL Classification: R14, R52.

*Brueckner is a professor of economics at UC Irvine (E-mail: jkbrueck@uci.edu). Fu is a professor of economics at Southwestern University of Finance and Economics (E-mail: fush@swufe.edu.cn). Gu is an assistant professor of economics at the Institute of Economic and Social Research at Jinan University (E-mail: yizhengu@gmail.com). Zhang is an associate professor of economics at Clark University (E-mail: juzhang@clarku.edu). We thank Paul Cheshire, Jeffrey Cohen, Gilles Duranton, Yuming Fu, Steve Ross, Xin Zhang, and audiences at the University of Connecticut, USC, University of Nevada-Las Vegas, the 2015 Urban Economics Association Conference, the 2015 ASSA Annual Meetings, and the CES North American conference at Purdue University for their comments and suggestions.

1 Introduction

Land-use regulation has been a long-time focus of research by economists and other scholars. Regulations are imposed in virtually every country in the world and take a variety of forms. They include traditional zoning laws, which are designed to allocate land to different uses while spatially separating them; restrictions on the density of development, which range from building-height limits to minimum lot-size requirements to street set-back rules; and restrictions on the volume of development, which include urban growth boundaries that limit the land area available for development and annual caps on building permits. Empirical research on land-use regulation has mainly focused on its impact on the prices of both housing and land, although a few studies measure its effect on the rate of new construction (see Gyourko and Molloy (2014) for an up-to-date survey). The evidence shows that regulations tend to raise housing prices, a consequence of their tendency to restrict housing supply, an effect that is separately documented in other studies.

The fact that regulations have price effects indicates that they are binding on development decisions. While this is an important finding, the literature to date contains few attempts to measure the *stringency* of land-use regulations, namely, the *extent to which they cause development decisions to diverge from free-market outcomes.* For example, highly stringent density restrictions would reduce development density far below the unregulated level, while less-stringent regulations would have a milder effect. A highly stringent urban growth boundary would constrain a city's footprint to be much smaller than its free-market size, while a less-stringent one would leave the footprint almost unaffected. Stringent zoning regulations could seriously skew a city's division of land between residential and commercial uses away from a free-market division.

One line of work that provides a measure of regulatory stringency was originated by Glaeser et al. (2005). They compare the marginal value of floor space estimated from an hedonic model to construction cost per square foot for residential buildings in Manhattan, with the gap (denoted the "regulatory tax") being an index of the extent to which regulations restrict development density below market levels.[1] The present paper develops and applies a distinctly different method for evaluating the stringency of land-use regulation. The method is developed theoretically, and it is then applied to an extraordinary dataset of land-lease transactions in China. We focus on the regulated floor-area ratio (FAR) for leased parcels, which limits the ratio of the floor area within the proposed building to the parcel's lot size. Although FAR is affected by the amount of open space left on the lot, it is effectively a measure of the allowed building height. A stringent FAR limit will thus constrain the building height to be much lower than the one the developer would choose in the absence of regulation. The unconstrained FAR is, of course, unobservable in the presence of the regulation, which means that the stringency of FAR limit cannot be gauged

[1] Further references to related work can be found in Gyourko and Molloy (2014).

directly. However, we demonstrate theoretically that the stringency of the limit can be inferred from the connection between land prices for leased parcels (which are available in the data) and their FAR limits, and we then use this connection to evaluate the stringency of FAR regulation in Chinese cities.

Because FAR regulation reduces the profitability of development, it reduces the developer's willingness-to-pay for the land and thus its value. Accordingly, a higher allowed FAR, by loosening the constraint on development, will raise the land price for the parcel. But our theory shows that a more-precise conclusion can be derived. We show that the elasticity of land price with respect to the FAR limit depends on the *ratio of the unconstrained and regulated FAR levels*. In particular, this elasticity is large when that ratio is large, or when the unconstrained FAR is high relative to the regulated FAR. Thus, relaxing a highly stringent FAR limit (one with a high ratio) leads to a greater percentage increase in land price than relaxing a less-stringent limit, an intuitively sensible conclusion.

We exploit this result using a land-lease dataset that consists of over 50,000 transactions across more than 200 cities during the 2002-2011 period. Our results allow us to gauge the restrictiveness of FAR regulation in China. We view FAR restrictiveness as being city-specific, running a land-value regression using lease transactions from all cities but allowing each city to have a different elasticity of individual parcel values with respect to parcel-specific FAR limits. The estimated elasticity coefficients then tell us which Chinese cities are most restrictive in their regulation of FAR. Under a second approach, we focus on a single large city (Beijing), allowing the land-price/FAR elasticity (and thus FAR restrictiveness) to vary according to site characteristics such as distance from the historic city center. In a companion regression to the first exercise, we relates the *restrictiveness* of FAR at the city level (as captured by city-specific coefficients in the land-price regression) to city characteristics. Finally, using a different dataset for Beijing that shows FAR limits for existing properties rather than new leases, we explore the factors that cause regulated FAR levels to change over time.

While our method could be applied to land-value/FAR data from any country, China's rapid urban growth generates an ideal dataset, with a large volume of transactions and considerable regulatory detail. Beyond its methodological contribution, the paper's focus on China helps to overcome a shortage of information about land-use regulation in one of the world's fastest growing economies. Only two rigorous studies (to the best of our knowledge) have previously investigated China's FAR restrictions. Fu and Somerville (2001) develop a theoretical model and then show empirically that restricted FAR values deviate from the developer's optimal value in a way that reflects the local government's goals. In a more recent paper, Cai, Wang, and Zhang (2016) investigate abrogations of FAR restrictions in China as a result of corruption. Using a unique dataset, they find that FAR is higher for transactions that involve corruption and that corruption is more likely to influence on FAR

for parcels in desirable locations.[2]

The plan of the paper is as follows. Section 2 provides an overview of the institutional setting in which land-lease transactions occur. Section 3 presents the theoretical model and discusses empirical implementation. Section 4 discusses the determinants of regulated *FAR* levels. Section 5 describes the national dataset and presents the results of the intercity regressions. Section 6 presents the regression results using the Beijing portion of the national data and then presents regressions using the separate Beijing dataset on *FAR* values for existing properties. Section 7 offers conclusions.

2 Institutional Background

China is experiencing rapid urbanization, with the share of the urbanized population rising from 21 percent in 1982 to over 50 percent today. This fast urban population growth has been accommodated by an unprecedented spatial expansion of the country's urbanized areas. In 1982, China's built-up urbanized area was 7,438 square kilometers. By 2011, it had risen to 43,603 square kilometers.[3]

This explosive urbanization was fueled by rapid conversion of land from rural to urban use, a process facilitated by local governments. By Chinese law, urban land is owned by the state, and rural land is owned by local economic collectives. To facilitate urban expansion, local governments acquire land from farmers at the urban fringe, paying compensation that is often substantially below market value (Ding 2007, Hui et al. 2013). The local governments then transfer land-use rights to independent developers via a leasehold, generating revenue that can be used for public investment and other purposes.[4] In earlier years, lease payments were decided through negotiations between land developers and government officials, which were conducive to corruption. Since 2004, local governments have used land auctions to make the transactions of land-use rights more transparent. The maximum term of the land lease is 70 years for residential uses, 50 years for industrial uses, and 40 years for commercial uses.[5]

A local government's land-use plan stipulates how a developer can use the leased land. The plan usually specifies the usage type, indicating whether the land is for residential, commercial, or industrial development, and it contains density restrictions, including the *FAR*, green coverage, and sometimes a separate explicit height limit. In other countries

[2] A few related studies examine *FAR* regulation in other countries. Using data on 273 land lots in the Tokyo area, Gao et al. (2006) estimate hedonic regressions to explore the effect of *FAR* restrictions on land prices. Brueckner and Sridhar (2012) measure welfare gains from relaxation of *FAR* restrictions in India. Barr and Cohen (2014) describe the *FAR* gradient and its evolution in New York City.

[3] See Ministry of Housing and Urban-Rural Development (2012) and National Bureau of Statistics of China (1983, 2012).

[4] Following a major tax reform in 1994, which weakened the tax base for local governments, local government officials learned that selling land-use rights is an effective way to generate revenue (Cao et al. 2008). In recent years, around 50 percent of local government revenue has come from land leases (Liu et al. 2012).

[5] When different branches of the government need land for construction of public infrastructure or military facilities, land-use rights can be obtained through a direct allocation.

such as the United States, land-use regulations also restrict development density, but these restrictions typically apply to many land parcels in a large section of a city. The unique characteristic of urban planning in China is that controls and restrictions are designed and implemented at the land parcel level. For our study, this unique institutional arrangement allows us to study *FAR* restrictions at the land parcel level, both theoretically and empirically.

As will be seen shortly, a local government interested in maximizing revenue from land leases would impose *no land-use restrictions at all*, recognizing that unrestricted profit-maximization on the part of developers leads to the highest land price. *FAR* restrictions will be desirable, however, once it is recognized that the high densities associated with high *FARs* impose costs on the local government, including the cost of providing supporting infrastructure to the newly built community. As a result, local officials will not allow developers to set an unrestricted, profit-maximizing *FAR*, which would maximize land revenue, but will instead sacrifice revenue by restricting the allowable *FAR*, with the goal of limiting the infrastructure costs associated with higher densities.[6] In this sense, local officials behave as *net revenue* maximizers, taking the public costs associated with land development into account.[7] The resulting restrictions then generate an association between land price for a site and its *FAR* limit, and by studying the strength of this association, we can infer the restrictiveness of the limit.

3 Measuring *FAR* stringency

3.1 Theory

To explore the connection between land price and *FAR*, consider the standard urban land-use model, as in Brueckner (1987). While this model is static, ignoring the long-lived nature of housing, the following analysis can be adapted easily to the case where a housing investment earns revenue over an extended period, as in Arnott and Lewis (1979). Let r denote the land price per acre and p denote the price per square foot of housing, which depends on a vector Z of locational attributes, including distance to the CBD, that affect the attractiveness of the site (thus, $p = p(Z)$). Let $h(S)$ denote square feet of housing output per acre as a function of structural density S, which equals housing capital per acre (h is concave, satisfying $h' > 0$ and $h'' < 0$). The housing developer's profit per acre is

[6] It is a well-known theoretical point that *FAR* and other housing density restrictions can be explained by invoking population-density externalities. See, for example, Bertaud and Brueckner (2005), Joshi and Kono (2009), Kono and Joshi (2012), Kono et al. (2010), Mills (2005), Pines and Kono (2012), and Wheaton (1998).

[7] Lichtenberg and Ding (2009) have similarly treated local government officials in China as rational decision makers in the context of land conversion for urban uses, and Zhang (2011) assumes local government officials to be rational revenue maximizers in a study of inter-jurisdictional competition for FDI in China. As shown by Li and Zhou (2005) and follow-up research, better economic performance increases a local leader's probability of being promoted and decreases the probability of his or her career termination.

given by

$$\pi = ph(S) - iS - r, \tag{1}$$

where i is the cost per unit of capital. The first-order condition for choice of S in the absence of an *FAR* limit is

$$ph'(S) = i, \tag{2}$$

and the S satisfying (2) is denoted S^*. The land price is then given by the zero profit condition:

$$r = ph(S^*) - iS^*. \tag{3}$$

An *FAR* limit imposes a maximal value for $h(S)$, denoted $\overline{h}$, which in turn imposes a maximal value of S. This value is denoted $\overline{S}$, and it satisfies $h(\overline{S}) = \overline{h}$. The effect of $\overline{S}$ on the land price r is considered first, with the link between r and $\overline{h}$ analyzed below. Faced with the *FAR* limit, developers will set $S = \overline{S}$, and the land price will be given by

$$r = ph(\overline{S}) - i\overline{S}. \tag{4}$$

The derivative of land price with respect to $\overline{S}$ is

$$\frac{\partial r}{\partial \overline{S}} = ph'(\overline{S}) - i > 0, \tag{5}$$

where the inequality follows because the *FAR* constraint is binding, with S restricted below its optimal value. If the *FAR* limit is not binding, then it will have no effect on development decisions and thus no effect on r. In addition, the land price will depend on the vector Z:

$$\frac{\partial r}{\partial Z} = \frac{\partial p}{\partial Z} h(\overline{S}). \tag{6}$$

A higher value of a favorable site characteristic j such as accessibility to employment, for which $\partial p/\partial Z_j > 0$, will raise the land price.[8]

Consider the elasticity of land price with respect to $\overline{S}$, which is given by

$$E_{r,\overline{S}} \;\equiv\; \frac{\partial r}{\partial \overline{S}} \frac{\overline{S}}{r} \;=\; \frac{[ph'(\overline{S}) - i]\overline{S}}{ph(\overline{S}) - i\overline{S}}. \tag{7}$$

Since concavity of h means that $h'(\overline{S})\overline{S} < h(\overline{S})$, $E_{r,\overline{S}}$ in (7) is less than unity, so that the elasticity of land value with respect to a binding S limit is less than one.

To get additional information, $ph'(S^*) = i$ can be used to eliminate i in (7). Doing so,

[8] An equivalent, but less familiar, modeling approach treats h rather than S as the choice variable, making use of a convext cost function $c(h)$ (profit per acre is then $ph - c(h) - r$).

the expression becomes

$$E_{r,\overline{S}} = \frac{\left[ph'\left(\overline{S}\right) - ph'\left(S^*\right)\right]\overline{S}}{ph\left(\overline{S}\right) - ph'\left(S^*\right)\overline{S}} = \frac{\left[h'\left(\overline{S}\right) - h'\left(S^*\right)\right]\overline{S}}{h\left(\overline{S}\right) - h'\left(S^*\right)\overline{S}}, \tag{8}$$

showing that $E_{r,\overline{S}}$ depends on S^* as well as $\overline{S}$ (note that p cancels). At this point, it is useful to impose a standard functional form for h. If $h(S) = S^\beta$, with $\beta < 1$, then (8) becomes

$$E_{r,\overline{S}} = \frac{\left[\beta\overline{S}^{\beta-1} - \beta\left(S^*\right)^{\beta-1}\right]\overline{S}}{\overline{S}^\beta - \beta\left(S^*\right)^{\beta-1}\overline{S}} = \frac{\beta\overline{S}^{\beta-1} - \beta\left(S^*\right)^{\beta-1}}{\overline{S}^{\beta-1} - \beta\left(S^*\right)^{\beta-1}} = \frac{(S^*/\overline{S})^{1-\beta} - 1}{\frac{1}{\beta}(S^*/\overline{S})^{1-\beta} - 1}. \tag{9}$$

Thus, the elasticity of land price with respect to $\overline{S}$ depends on the ratio of the developer's optimal S (S^*) to the restricted level, $\overline{S}$. Furthermore, differentiation of (9) shows that

$$\frac{\partial E_{r,\overline{S}}}{\partial(S^*/\overline{S})} > 0, \tag{10}$$

so that the elasticity is large when the restricted S lies far below the optimal value (making $S^*/\overline{S}$ large). In other words, the percentage increase in land price from relaxing a very tight $\overline{S}$ limit is greater than the percentage increase from relaxing a looser limit, a conclusion that matches intuition.

Since $h(\overline{S}) = \overline{h}$ implies $\overline{S}^\beta = \overline{h}$ under the chosen functional form, it follows that $\overline{S} = \overline{h}^{1/\beta}$. Therefore, the elasticity of land price with respect to $\overline{h}$, denoted $E_{r,\overline{h}}$, equals $1/\beta$ times the elasticity with respect to $\overline{S}$, so that

$$E_{r,\overline{h}} \equiv \frac{\partial r}{\partial \overline{h}}\frac{\overline{h}}{r} = \frac{E_{r,\overline{S}}}{\beta}. \tag{11}$$

Given (11), it follows that $E_{r,\overline{h}}$, like $E_{r,\overline{S}}$, is increasing in $S^*/\overline{S}$:

$$\frac{\partial E_{r,\overline{h}}}{\partial(S^*/\overline{S})} > 0. \tag{12}$$

Thus, the percentage increase in land price from relaxing a tight FAR limit is greater than the increase from relaxing a loose one. Note that since both $E_{r,\overline{S}}$ and β are less than 1, the elasticity $E_{r,\overline{h}}$ can be either larger or smaller than 1, in contrast to $E_{r,\overline{S}}$ itself.

As seen below, the empirical model will generate an estimate of $E_{r,\overline{h}}$, which is denoted θ. Treating θ as a known value and imposing a value for β, (9) can then be solved for the ratio $\overline{S}/S^*$, which then allows the ratio of the FARs to be computed. The solution is $h(\overline{S})/h(S^*) = [(1-\theta)/(1-\theta/\beta)]^{-\beta/(1-\beta)}$. Therefore, using the estimated θ and a value for β, the actual ratio of the regulated and free-market FARs can be derived.

While the possibility of bribery has apparently been reduced by adoption of an auction format for the lease transactions, it may still be present in some cases (Cai et al. 2013). To see how bribery affects the previous results, suppose the developer can raise the effective $\overline{S}$ by the factor $\sigma > 1$ by paying a bribe equal to $1-\lambda$ of his revenue. This bribe is paid to an official different from the one who sets $\overline{S}$, a decision explained below (the mayor, for example, rather than the city planner). The effective FAR limit is then $\sigma\overline{S}$, while the observed limit remains at $\overline{S}$, and p is replaced by λp. It can be shown that, in the elasticity formula (9), the 1's in both numerator and denominator are replaced by $\sigma^{1-\beta}/\lambda > 1$. While this change affects the magnitude of the elasticity, it does not alter the central conclusion from (12) that the elasticity $E_{r,\overline{h}}$ is increasing in $S^*/\overline{S}$. However, holding $S^*/\overline{S}$ fixed, it is easily seen that the presence of bribery reduces the elasticity. This conclusion follows because the elasticity expression is decreasing in $\sigma^{1-\beta}/\lambda$ and because this expression takes the smaller value of 1 in the absence of bribery.

3.2 Empirical implementation

The result in (12) can be exploited via estimation of a land price regression relating the log of land price to the log of the FAR limit along with the vector Z. In a single city, the regression would have the form

$$\ln r_i = \alpha + \theta \ln FAR_i + Z_i\gamma + \epsilon_i, \tag{13}$$

where θ is the elasticity of land price with respect to FAR, γ is the vector of coefficients on site characteristics, ϵ is the error term, and i denotes individual land parcels. Our first exercise is to estimate this model using the entire national data set, assuming a uniform elasticity θ but allowing intercepts to differ across cities and the administrative districts within them, as well as by time (a typical city contains around 5 districts). Under this approach (13) becomes

$$\ln r_{jcdt} = \alpha_{cdt} + \theta \ln FAR_{jcdt} + \epsilon_{jcdt}, \tag{14}$$

where j denotes parcels, c cities, d districts, and t years. City-district by year fixed effects are denoted by α_{cdt}. Note that these fixed effects subsume the Z variable from (13).

A second approach is to allow the elasticity θ to be city-specific, so that (14) becomes

$$\ln r_{jcdt} = \alpha_{cdt} + \theta_c \ln FAR_{jcdt} + \epsilon_{jcdt}. \tag{15}$$

To interpret (15), suppose that some cities are highly restrictive in their FAR regulations, with the $\overline{S}$ values for individual parcels far below the optimal S^* values, while the other cities are less restrictive, with $\overline{S}$'s closer to the S^*'s. Then, the estimated θ_c's for the cities in the first group would be larger than the estimated θ_c's for cities in the second group. Therefore, *differences across cities in estimated θ values reflect differences in the* *restrictiveness of their FAR regulations.*

Alternatively, a variant of the regression in (13) could be used to explore how *FAR* restrictiveness *varies across locations within a single large city*, which has enough parcel observations to carry out a regression. To make such an inference, the impact of *FAR* on land price could be allowed to depend on site characteristics, measurement of which is infeasible in the large national dataset but is practicable in a smaller single-city sample. For example, suppose *FAR* restrictiveness depends on distance from the city center, denoted by x, with the relationship between $\overline{S}$ and S^* depending in some fashion on this distance measure (x is one element of Z). This outcome could be captured by dropping the *cd* index and rewriting the regression in (14) as

$$\ln r_{it} = \alpha + \beta_t + \theta \ln FAR_{it} + \eta(x_i * \ln FAR_{it}) + Z_i\gamma + \epsilon_{it}, \qquad (16)$$

with *FAR* now also appearing in an interaction term involving x. If the estimated η is negative, the implication is that *FAR* restrictiveness is lower farther from the city center, while a positive η would indicate that greater restrictiveness farther from the center.

As seen in section 3.1, the land-price elasticity for an individual parcel depends on the ratio $S^*/\overline{S}$. If this ratio were identical for all parcels (with the regulated *FAR* a uniform fraction of the free-market value), then the elasticity would be constant across parcels. More realistically, the ratio will vary across parcels (with some central tendency), so that the estimated θ for a city will be an average elasticity across its parcels. In the same way, elasticities will vary across parcels if some land leases are affected by bribery while others are not (recall the change in the elasticity formula in (9)). The estimated elasticity for a city with a mix of corrupt and non-corrupt lease transaction will then be an average value across these types of parcels. Recall, though, that regardless of whether or not bribery is present, the elasticity is still increasing in $S^*/\overline{S}$, thus indicating the stringency of the (stated) *FAR* limit.

Another possibility is that some cities are uniformly more corrupt than others, so that most lease transactions in one city involve bribery while few do in another city. Recalling that bribery reduces the magnitude of θ, the difference in θ between the cities will then reflect the difference in the stringency of their *FAR* limits *along with* any difference in corruption. However, if the auction method indeed limits bribery and if corruption is more parcel-specific than city-specific, this potential barrier to interpretation of the results may not be a concern. This view is buttressed by a 2009 investigation of 73,139 land leases, which revealed that planned *FAR*s were illegally adjusted in only 2.72% of the leases, suggesting the bribery is fairly rare (http://china.findlaw.cn/fagui/p_1/340505.html, in Chinese). See also Cai et al. (2016).

4 Determinants of *FAR* limits

4.1 Theory

The analysis so far has taken the *FAR* limit as given, but there is reason to believe that government officials pursue their own goals when setting *FAR* limits, potentially making *FAR* endogenous. Consider a local government official's decision to choose the *FAR* for a land parcel. Like the developer, the official understands the determination of land prices and also recognizes that the development generates some extra public infrastructure costs for the local government in the amount of $K(S)$ (for roads, sewers, water lines, etc). $K'(S) > 0$ holds because denser development requires more and/or better supporting infrastructure. We assume that the local government official seeks to maximize the net revenue from land development:

$$r - K(S) = ph(S) - iS - K(S). \tag{17}$$

Thus, the government official's optimal structural density $\overline{S}$ satisfies the condition

$$ph'(\overline{S}) - K'(\overline{S}) = i. \tag{18}$$

Recall that, at the developer's optimal density S^*, $ph'(S^*) = i$. Given that $h' > 0$, $h'' < 0$, and $K' > 0$, it follows that $\overline{S} < S^*$. As a result, the government-imposed *FAR*, $\overline{h} = h(\overline{S})$, is below $h(S^*)$, and it will thus be binding.

Equation (18) implies that the variables Z affecting the housing price p (e.g., local amenities) will in turn influence the *FAR* limit chosen by the government, and that any variables V affecting the government's marginal infrastructure cost (K') will also affect the *FAR* limit. Therefore[9]

$$\overline{h} = \overline{h}(Z, V). \tag{19}$$

4.2 Empirical implications

Some site characteristics contained in Z will be unobserved and thus present in the error term ϵ in (13). But, from (19), these unobserved elements of Z will also influence $\overline{h}$. Thus,

[9]This analysis, as well as that in section 3, treats the housing price p as fixed and unaffected by the change in $\overline{S}$ for an individual parcel. While this assumption is realistic, it may not be correct to view housing prices as independent of a city's overall land-use regulation policy. For example, a city wishing to exercise market power over prices may restrict housing supply by limiting *FAR* values throughout the city, thus raising p at all locations. Although possible in a "closed" city with a captive population, this exercise of market power is not possible in an "open" city, where migration is free and residents therefore enjoy an externally fixed utility level. Viewing $\overline{S}$ as a city-wide choice, exercise of market power would introduce a $\partial p/\partial \overline{S}$ term in (18), but this term may simply call for adding city-level variables (determinants of market power) to the determinants of $\overline{h}$ in (19). As for the land-price regression in (10), which is identified by variation in prices and *FAR* values within districts and across years, the market-power issue is not relevant. The exercise of market power will simply raise city-wide land prices, thus being captured by the city fixed effect. The identifying variation holds housing prices p fixed, regardless of whether or not their level has been determined by a city's exploitation of market power.

the FAR limit in (13) (which is $\overline{h}$) will be correlated with the error term. As a result, the coefficients from OLS estimation of (14), (15), and (16) are likely to be biased.

One solution to this problem is to rely on an instrumental variables approach, perhaps using as instruments for FAR variables that appear in V in (19). In the single-city regression for Beijing, we use this IV approach, relying on district dummy variables as instruments, which could capture infrastructure costs and other factors affecting regulation. Beijing has 18 districts, much more than the typical city (which has 5). Since city-level instruments are difficult to find, we take a different approach in the intercity regressions in dealing with potential correlation between FAR and omitted variables. Our approach is to use a locational fixed effect more refined than the city-district by year effects used in our baseline regressions (which use only an average of 5 locational dummies per year). We identify small clusters of close-by land leases, most of which contain just two parcels. Using cluster instead of city-district fixed effects, we estimate the relationship between log land price and log FAR using only within-cluster variations, relying on a relatively large number of clusters. The idea is that, if two parcels are next to each other, then they probably have very similar site attributes, although the FAR values chosen by the city planners may differ. Therefore, if we focus on variations among leases in close physical proximity and still find that a higher FAR leads to a higher land price, then this effect is likely to be causal, netting out the effect of unobserved factors. More detail on this "matched pair" approach are provided below.

5 Intercity Analysis

5.1 Data sources

This section presents results from the intercity analysis, where (14) and (15) are estimated using the national dataset. To generate this dataset, we use both proprietary and public data sources. The main data come from the China Index Academy (CIA), the largest independent research institute in China focusing on real estate and land issues. CIA aims to provide comprehensive and accurate real estate and land data as well as related market consulting services. One of CIA's major products is its database on land transactions in over 200 cities across China. Our extract of the data was generated in early 2012. It contains information on over 120,000 land transactions during 2002-2011, although various exclusions due to missing data and other factors reduce the usable number of observations to around 50,000.[10] Our analysis focuses on residential and commercial land; lease transactions for other uses (industry, warehouse, public facilities, education, etc.) are dropped. For each land parcel, we know its location, usage type, planned floor area, planned FAR, planned green coverage, planned structural density, the auction start and end days, price per unit of

[10]CIA's data collection effort focuses primarily on transactions using land auctions. Since land auctions were not common before 2002, their data coverage in those early years appears to be very poor, leading us to drop pre-2002 observations.

Table 1: Average maximum allowed floor area ratios

	Land for residential uses		Land for commercial uses	
	By city size			
	Mean FAR	No. of obs.	Mean FAR	No. of obs.
Population $\geq$ 2 million	2.352	15,024	2.516	12,819
2 million $>$ Pop. $>$ 1 million	2.456	7,820	2.427	6,644
Population $\leq$ 1 million	2.425	6,505	2.316	5,117
	By year of transaction			
	Mean FAR	No. of obs.	Mean FAR	No. of obs.
2002-2003	1.846	733	2.419	405
2004-2005	2.083	1,920	2.104	1,804
2006-2007	2.298	3,732	2.425	3,253
2008-2009	2.368	6,508	2.488	5,509
2010-2011	2.487	16,906	2.488	13,609

Classification of city size is based on population in 2005.

planned floor area, price per unit of land, required deposit for bidders, minimum incremental bid, winner of the auction, selling price, and transaction date.

In some cases, the FAR restriction is specified as a single number. In other cases, it is given as a range, in which case we use the upper limit of the range. To reduce the influence of extreme observations, we dropped the outliers from the top and bottom one percent of land prices and from the top and bottom one percent of maximum allowed FAR.

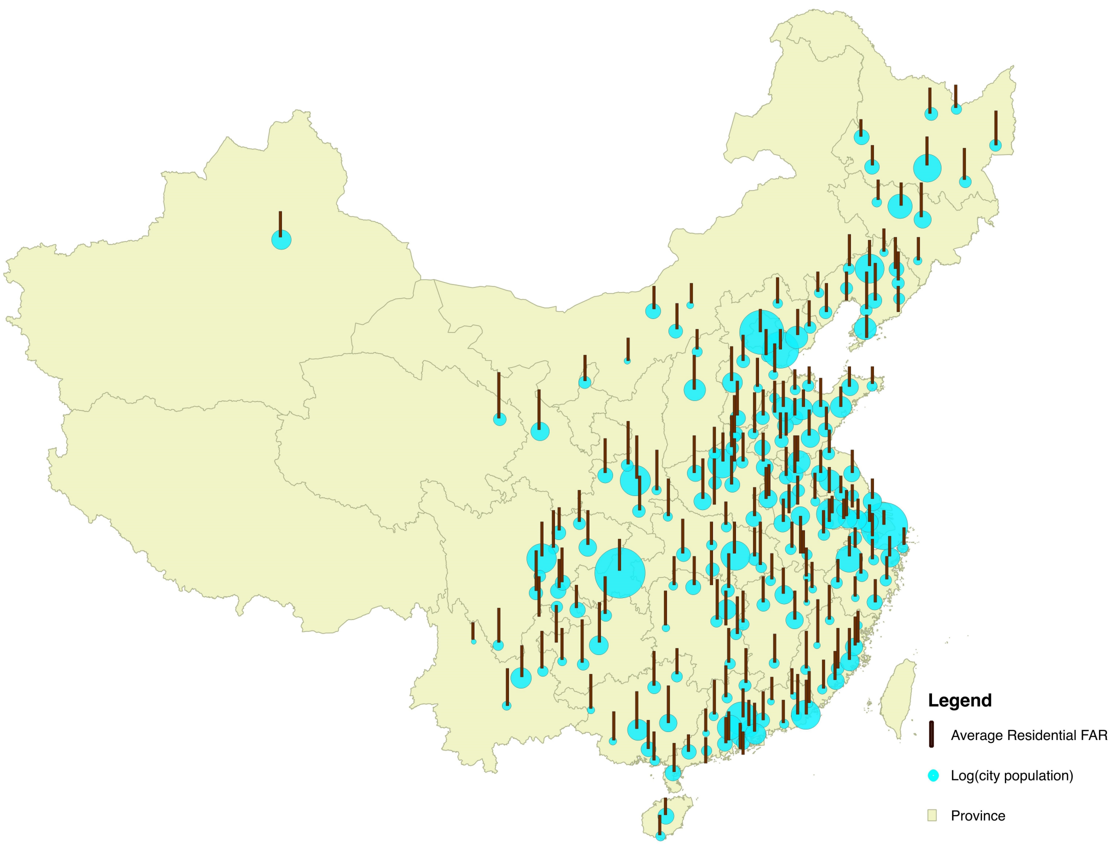
Table 1 presents descriptive statistics from the CIA data. The upper panel shows the average maximum allowed FAR by city size. For residential land uses, it is the medium-sized cities that allow the highest FARs; for commercial land uses, larger cities tend to have higher FARs. It should be noted, however, that since new land leases tend to be on homogeneous, converted agricultural land near the edges of cities, not in the high-rise centers, no particular connection of FAR to overall population is predicted.

The lower panel of Table 1 shows the average maximum allowed FAR in different time periods. For both residential and commercial land uses, the maximum allowed FAR has tended to rise over time.[11] During the 2002-2011 decade, housing prices grew increasingly faster in Chinese cities, and city planners might have adjusted their expectations of housing-price growth rates accordingly. Both higher and faster-growing housing prices would imply higher allowed FARs over time, as suggested by (18).

Figure 1 shows a map of China indicating cities where the CIA data on land auctions

[11] The higher mean FAR for commercial land in 2002-2003 comes from a very small sample, which is not representative because, at that time, some land transactions were not conducted through auction and thus would not be captured by the data.

Figure 1: Floor area ratio restrictions in Chinese cities



Note: The size of the circle represents the 2010 population of the city; the height of the bar represents average maximum allowed floor area ratios in the city over different years.

are collected. Each blue circle indicates the size of the city by 2010 population; the height of the bar represents the average *FAR* for residential land in the city. Cities covered by the data are mostly in the East or central region, and very few are in the West, reflecting the distribution of population and economic activity in the country.

5.2 Results using city-district fixed effects

Table 2 presents estimation results for the land-price regressions, relying on city-district by year fixed effects. Whereas our model was developed in the context of residential land uses, we run the same set of regressions with commercial land transactions for comparison.[12] We first estimate equation (14), where a uniform nationwide θ is assumed, and the results are presented in panel A. Controlling for over 3000 city-district by year fixed effects, we find that log land price is indeed positively associated with log *FAR*, indicating that *FAR* restrictions are binding on average. This finding emerges for both residential and commercial leases, although the coefficient for residential leases is much larger. Note that the standard errors for the regression are clustered at the city-district level.[13]

Panel B of Table 2 shows the results from estimation of (15), where the θ coefficients are allowed to vary across cities (standard errors are now clustered by city). To improve the precision of estimation, we estimate separate coefficients only for cities with 100 or more lease transactions in the sample and lump all other cities into one group. For residential leases, we estimated 73 city-specific coefficients. The average of these estimates is 0.7481, almost identical to the single coefficient estimated in panel A (0.7466). The coefficients range from -0.0110 to 1.5543, and almost all are positive. For commercial leases, we estimated 62 city-specific coefficients. The average is 0.5927, also fairly close to the single estimate in panel A (0.5669). All of the coefficients are positive, ranging from 0.1025 to 1.2307.

In panels (*i*) and (*ii*) of Figure 2, we plot the distributions of city-specific coefficients. For both residential and commercial land, there is a great deal of heterogeneity in the estimated coefficients. Although, for residential land, the average coefficient is 0.75, some cities at the lower end of the distribution have coefficients very close to zero, suggesting that land prices and regulated *FAR* are hardly correlated in those cities. By contrast, at the upper end of the distribution, some cites have coefficients higher than 1. Overall, these results suggest that the stringency of *FAR* regulations varies a great deal across cities. Whereas the limits are hardly restrictive in some cities (generating θ coefficients close to zero), in other cities they represent a serious constraint on development density, generating

[12]There are many land leases that are planned for "mixed" (both residential and commercial) uses. We include these observations in both the residential and commercial samples.

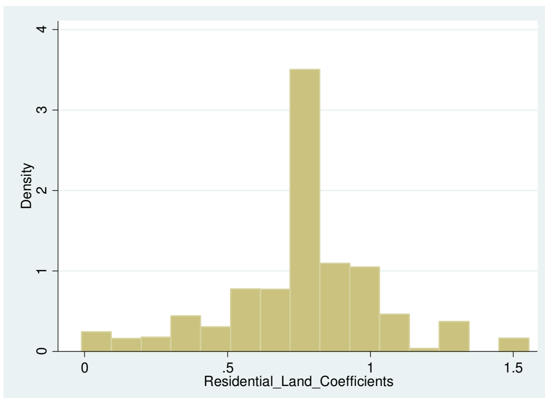
[13]For 36% (10,507 out of 29,349) of the residential land parcels and 37% (9,086 out of 24,580) of the commercial land parcels, a minimum *FAR* requirement is also specified in the CIA data. We estimate a set of regressions similar to those in panel A, using minimum instead of maximum *FAR* as the independent variable. The coefficients, 0.589 and 0.500 for residential and commercial land respectively, are also positive and highly significant. These results suggest that the minimum *FAR* requirement is not binding, in which case the coefficient would be negative.

Table 2: Regressions of land price on *FAR*

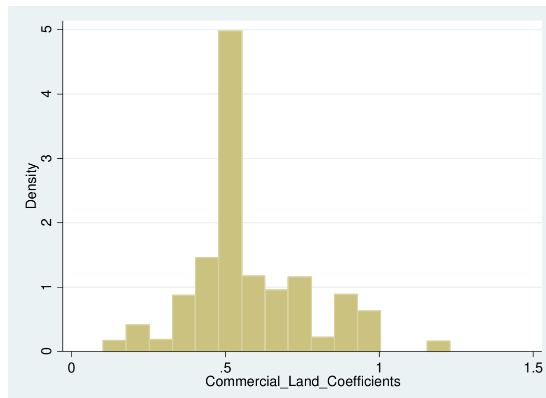
Dependent variable: Log unit land price		
Variable	(1) Residential Land	(2) Commercial Land
A. Same coefficient in all cities, full sample		
Log floor area ratio	0.7466***	0.5669***
	(0.0303)	(0.0204)
City-district by year fixed effects	Yes	Yes
Adjusted R^2	0.6345	0.5850
Number of observations	29,349	24,580
B. Allow for different coefficients across cities, full sample		
Log floor area ratio	73 city-specific coefficients	62 city-specific coefficients
	Mean: 0.7481	Mean: 0.5927
	Std. dev.: 0.3250	Std. dev.: 0.2502
City-district by year fixed effects	Yes	Yes
Adjusted R^2	0.6424	0.5911
Number of observations	29,349	24,580
C. Same coefficient in all cities, matched sample		
Log floor area ratio	0.3572***	0.3641***
	(0.0782)	(0.0649)
Cluster fixed effects	Yes	Yes
Adjusted R^2	0.9431	0.9322
Number of observations	5,675	4,052
D. Allow for different coefficients across cities, matched sample		
Log floor area ratio	38 city-specific coefficients	27 city-specific coefficients
	Mean: 0.2876	Mean: 0.2572
	Std. dev.: 0.3472	Std. dev.: 0.4323
Cluster fixed effects	Yes	Yes
Adjusted R^2	0.9455	0.9351
Number of observations	5,675	4,052

Standard errors (in parenthesis) are clustered by city-district in panels A and B and by city in panels C and D. ***: $p < 0.01$. Although not reported in the table, a constant is included in every regression. The regressions in column (1) of panels A and B include 3,500 city-district by year fixed effects; the regressions in column (2) of panels A and B include 3,225 city-district by year fixed effects. The regressions in column (1) of panels C and D include 1,874 cluster fixed effects; the regressions in column (2) of panels C and D include 1,410 cluster fixed effects. In the matched sample, observations are classified into the same cluster if they are in the same city, same district, same year, planned for the same type of land use, and the first 12 Chinese characters of their addresses are identical. The regressions in panel B allow each city with 100 or more observations to have a specific coefficient. The regressions in panel D allow each city with 50 or more observations to have a specific coefficient.

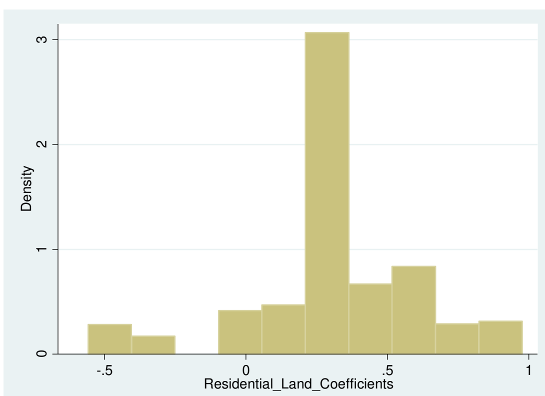
Figure 2: Distributions of city-specific coefficients



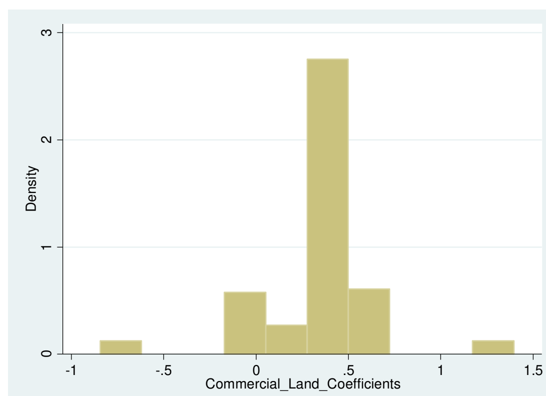
(i) 73 city-specific coefficients for residential land, full sample



(ii) 62 city-specific coefficients for commercial land, full sample



(iii) 38 city-specific coefficients for residential land, matched sample



(iv) 27 city-specific coefficients for commercial land, matched sample large positive coefficients.

5.3 Results using cluster fixed effects (matched-pair approach)

We now turn to the matched-pair approach for dealing with potential endogeneity of FAR. As explained above, the approach creates clusters of nearby parcels, whose unobservable characteristics are likely to be similar. Parcels in each cluster are indicated by a separate fixed effect, with the clusters being much smaller than city-districts and thus more numerous. Since clusters are year-specific, year fixed effects are unneeded. Two or more parcels of land are categorized into the same cluster if

- they are located in the same city, the same district, and sold in the same year;
- they have exactly the same land-use type;[14]
- the first 12 Chinese characters in their addresses are identical.[15]

Since parcels that are not near other parcels are not part of a cluster, these parcels are dropped, leading to 5,675 observations in 1,874 clusters for the residential land sample and 4,052 observations in 1,410 clusters for the commercial land sample.[16] We refer to these data as the matched sample.

A natural question is why parcels in close proximity would have different FAR limits, as required to estimate a land-price effect based on intra-cluster FAR variation. Planners may impose different limits due to a housing sunlight standard, under which a southern parcel in a cluster should have a lower FAR than its northern neighbor; to differences in the sizes and shapes of parcels; to view considerations, which dictate a mix of building heights in an area; and to differences in required nearby infrastructure (roads and parks).

[14] Even within residential or commercial land uses, there are many different specific use types. For example, within residential use, there are "residential housing," "ordinary housing," "affordable housing," "residential housing and retailing," "residential housing and daycare," "residential housing and public facilities," etc. We consider each use type a unique one as long as it is specified using a unique sequence of Chinese characters. This is a very narrow definition. For example, among Beijing's 327 residential land transactions, there are 138 distinctive use types by our definition.

[15] The address is taken from land-auction listings. Since information on province and city is self-evident in such listings, the address information starts with city district name, county name (in case it is a conversion of rural land to urban use), or street name. Since, at the time of land auction, the development project usually does not yet have a formal address, this variable often simply lists some streets as the boundaries of the land parcel. Two parcels for which part of the address or the whole address (in case the address is no more than 12 characters long) are identical are almost surely located along the same street or in the same village (if on the urban fringe). The actual spatial proximity of parcels within clusters cannot be checked for most of the data because of the absence of geocoding. But since geocoding was carried out for the Beijing subsample (see section 6.1 below), we can calculate intra-cluster distances, measured using the minimum distance between the edges of any two parcels within a cluster. The median distance is 397 meters, and only one parcel is more than 2.5 km away from other parcels in the cluster. Although there is considerable variation, these intra-cluster distances are reasonably small, especially given that most of the land parcels are at the urban fringe.

[16] For residential land, 66.49% of the clusters have only a pair of parcels, 22.41% have 3 or 4 parcels, and the rest (11.10%) have 5 or more parcels. For commercial land, 68.72% of the clusters have only a pair of parcels, 21.35% have 3 or 4 parcels, and the rest (9.93%) have 5 or more parcels.

Regression results using the matched sample are presented in panels C and D of Table 2. Panel C shows the results from single-coefficient regressions, which should be compared to those in panel A. For both residential and commercial land, the coefficient is now much smaller. For residential land, the coefficient is 0.3572, compared to 0.7466 estimated using the whole sample and controlling for city-district by year fixed effects. For commercial land, the coefficient is 0.3641 compared to 0.5669. Both estimates are still highly significant. These smaller coefficients indeed suggest that there is some omitted-variable bias in the coefficients estimated using the whole sample.

Panel D of Table 2 shows the results of the regression with city-specific θ coefficients estimated from the matched sample. To improve the precision of estimation, we only estimate separate coefficients for cities with at least 50 observations, with the other cities lumped together. Consequently, we have 38 city-specific coefficients for residential land and 27 coefficients for commercial land. Panels (iii) and (iv) in Figure 2 show the distributions of coefficients estimated using the matched sample, for residential and commercial land respectively. For residential land, the coefficients estimated using the matched sample are mostly smaller than those estimated using the whole sample; the distribution in panel (iii) looks like the one in panel (i) shifted to the left. For commercial land, the coefficients estimated using the matched sample not only have a lower average but also are more dispersed. Overall, most cities still have positive coefficients, as suggested by our model.

As explained above, the estimated θ can be used along with a value of β to infer the value of the $h(\overline{S})/h(S^*)$ ratio. Assuming $\beta = 0.6$ (as in Bertaud and Brueckner (2005)), and using the average residential θ value from panel D of Table 2, the formula from above yields $h(\overline{S})/h(S^*) = 0.62$. Thus, the results suggest that the average residential FAR limit is about two-thirds of the free-market value.

5.4 Comparisons across cities

It is interesting to observe exactly where different cities lie in the distribution of coefficients. To address this question, we list all the coefficients for the residential regressions in the Appendix Table A-1. The list on the left of the table comes from the regressions in panel B of Table 2, which use city-district by year effects, while the second list comes from the matched-pair regressions of panel D.

Among the cities with the smallest coefficients in first list, Qinhuangdao, Erdos, and Yingkou are well-known for their fast pace of urban construction. In recent years, they are often cited as examples of the Chinese housing bubble, having so many newly built but empty housing units that the cities are often referred to as "ghost cities."[17] These cities have small coefficients perhaps because they have been in a building spree where FAR

[17] *Time* magazine recently posted a set of photos of Erdos on its website (see http://content.time.com/time/photogallery/0,29307,1975397,00.html). They call it "a modern ghost town."

restrictions are loose and thus often not binding. Xi'an, also with a small coefficient, is a city that has a long and rich history. It served as the capital of China during Zhou, Qin, Han, Sui, and Tang dynasties. More importantly, Xi'an is the only large city in China today that has preserved a magnificent city wall. The wall was constructed in the late 14th century, and it surrounds the present city center, being 12 kilometers in circumference, 12 meters high, and 15-18 meters thick at the base. While land is generally more valuable close to city center because it is closer to employment and many city amenities, planners may have imposed lower floor area ratios in this area to protect the beauty of the city wall and other historical sites in Xi'an. This mechanism implies a negative relationship between log land price and log FAR, which could cancel the positive correlation posited in our model and thus lead to a coefficient close to zero.

Cities with the largest coefficients include Nantong, Jiujiang, Kunming, Nanning, and Yancheng. These are all low-profile cities, whose relatively short buildings suggest that FAR limits are highly stringent. By contrast, it is perhaps somewhat surprising to see that the largest Chinese cities, such as Shanghai, Beijing, Tianjin, Chongqing, and Guangzhou, all have below-average coefficients. That is, despite the government's explicit policy to control growth in these mega-cities, their FAR limits do not seem to be more restrictive than those in many other cities.

The second list in the Appendix Table contains the 38 city-specific residential coefficients from the matched sample, for comparison with those estimated from the whole sample. Xi'an, which has the second smallest coefficient in the left column, now has too few observations in the matched sample and does not have a separate coefficient. Erdos' coefficient becomes bigger. Qinhuangdao and Yingkou are now joined by Foshan, Shanghai, and Tianjin to form the five cities with the smallest coefficients. Looking down the lists, we see that the relative ranks of many cities have changed between the two sets of estimates. Zhengzhou, Harbin, Luzhou, Shenyang, and Huizhou have the largest coefficients in the right column. Overall, the estimates from the matched sample still show a great deal of heterogeneity across cites. Whereas FAR restrictions are hardly binding in some cities, they impose a serious constraint in other cities. In this latter group, housing density in newly developed areas would be higher if not for the stringent restrictions.

5.5 Allowing the FAR elasticity to vary across cities and time

Although city-specific θ's have been allowed, a further generalization would allow the elasticities to vary both by city and time. Data limitations make it undesirable to estimate θ's with both i and t subcripts, but a different approach is to interact FAR with a variable that may affect regulatory stringency and that varies across cities and time. One such variable would be a measure of employment-growth pressure, which may affect both the free-market and regulated FARs and thus their ratio. Rather than using a city's actual employment growth, reliance on a Bartik (1991) index, which weights sectoral employment growth rates at the national level by the city's sectoral employment shares, may be preferable. Appendix Table A-2 reports results when two variants of the Bartik index are interacted with FAR, and the results tend to show positive interaction coefficients. These coefficients suggest that the stringency of FAR regulation, as reflected in the elasticity of land price with respect to FAR, is greater during periods of rapid employment growth. $S^*/\overline{S}$ thus tends to be high when growth is rapid, possibly because S^* rises faster than $\overline{S}$ in such periods. While this conclusion is suggestive, we believe that regulatory stringency is best viewed as changing slowly over time, making an empirical specification like this one less appropriate than one that treats θ as intertemporally constant.

5.6 Aggregate lease-revenue impact of raising *FAR*: An example

It is interesting to explore the effect of higher FAR limits on a representative city's revenue from land leases. Consider the city of Ningbo, a large coastal city in Zhejiang Province whose residential θ estimate from the matched sample is 0.288, almost exactly the mean of the city-specific residential θ's. During 2002-2011, 584 residential lease transaction occurred in Ningbo. Converting prices to their 2010 values, these transactions generated 103.32 billion yuan for Ningbo's government, about 10.33 billion yuan per year (equal to approximately one-third of the government's total revenue, from the 2011 *Urban Statistical Yearbook*). Now suppose that the FAR for each transaction were increased by 0.72 (equal to one standard deviation for the entire sample). Using the 0.288 coefficient for Ningbo, total lease revenue would have increased to 114.26 billion yuan, for a gain of 10.6%. Therefore, Ningbo sacrificed considerable revenue because of its FAR limits, presumably with the goal of saving infrastructure costs.

5.7 The determinants of *FAR* stringency

The next step in the analysis is to explore the determinants of FAR stringency, which is done by regressing the city-specific θ estimates on city characteristics. While it is also possible to regress actual FAR values on city characteristics to explore the determinants of the height limits, that exercise is not particularly informative.[18] The stringency analysis focuses on three main city characteristics: the presence of historical-cultural sites; whether the city has an official "tourist city" designation; and the share of the industrial sector (the "second" sector) in the city's GDP. We expect that historic sites will lead to stringent FAR regulation, as discussed earlier, and that a "tourist city" designation may have the same effect. We expect that a large industrial presence might relax FAR limits as cities attempt to build housing for workers in this important sector.

In addition to variables capturing these effects, we also include four "control" variables from the *China Urban Statistical Yearbook*, even though their effects are sometimes difficult

[18] With most lease transactions on the fringes of cities near homogeneous agricultural land, it is not clear theoretically how city characteristics should affect the chosen FARs.

to predict. These variables are city population, city fiscal revenue (which excludes land-lease revenue), the number of city buses operated, and the city's miles of paved road. The last three variables are expressed in per capita terms, and all are logged. While most land leasing occurs on agricultural land near the city's edge, its overall population may still have an effect on stringency. Substantial other-source city revenue would help cover infrastructure costs, reducing the need to limit *FAR*s and thus reducing stringency. Low transportation costs (as captured by the last two variables) tend to raise the attractiveness of land near the urban fringe and thus free-market *FAR*s at these fringe locations (where leasing occurs), with possible effects on stringency.

Table 3 presents the regression results, which are shown for both the full and matched samples and for both residential and commercial leases. The observation counts are equal to the numbers of distinct cities in the two samples: 73 and 37, respectively, in the residential case. Panel A of Table 3 shows results for the case where the number of historical sites in the city is the focal variable. Its coefficient is positive and significant at the 10% level in the residential matched-sample regression, consistent with the expectation of stringent *FAR* regulation in historical cities. None of the control-variable coefficients is statistically significant, however. With the control-variable coefficients suppressed, panel B of Table 3 shows the estimated coefficients of a dummy variable indicating that the city had not been designated a tourist city by 2004, indicating low attractiveness for tourism.[19] While neither dummy coefficient is significant in the residential regressions, the matched-sample commercial regression has a coefficient that is negative and significant at the 5% level, as expected. Commercial *FAR* stringency is thus low in cities with few tourist attractions requiring protection.

Panel C of Table 3 shows the coefficients of the variable equal to the industrial share of city GDP. As expected, this variable's matched-sample residential coefficient is significantly negative (at the 10% level), indicating low *FAR* stringency in industrial cities. However, commercial *FAR* stringency is high in such cities, as seen in the matched-sample regression. Evidently, a high industrial share, by yielding a low commercial share, means little pressure to provide commercial space, allowing stringent commercial *FAR* regulation.[20] Only a few control-variable coefficients are significant in the regressions of panels C and D [21]

While the effects shown in Table 3 are not particularly robust, appearing only in a few regressions, they nevertheless provide some evidence that *FAR* stringency varies across cities in a fashion consistent with intuition. By contrast, other city characteristics such as

[19] Every few years, the central government adds a number of new cities to the list of tourist cities. If a large city, like those in the matched sample, had still not been designated as a tourist city by 2004, it must have very few tourist attractions (historical-cultural sites, as well as man-made/natural beauties such as famous gardens, lakes, and mountains). Tangshan is a good example.

[20] Note that the results in Appendix Table A-2 provide contrasting results, showing that residential *FAR* stringency is high when employment *growth* across all sectors is rapid. However, the fact that stringency is allowed to vary with time in those regressions makes them mostly noncomparable to those in Table 3.

[21] The coefficient of paved road has significant negative coefficients in the matched-sample commercial regressions in both panels B and C, consistent with expectations.

weather quality (measured by January temperature) that have no obvious association with FAR stringency in fact generate no significant coefficients in other, unreported regressions.

6 Beijing Analysis

6.1 Land prices and regulated *FAR* in Beijing

We now turn to the city of Beijing and analyze the land-price effects of FAR restrictions within this single city. We estimate equation (16), which allows the elasticity of land price with respect to FAR to vary with site characteristics. To construct the sample for our analysis, we extract all of the 327 residential lease transactions in the Beijing metropolitan area from the nationwide land-auction data. For each parcel of land, a detailed map is available from the online record of the land transaction, which we use to obtain its longitude-latitude coordinates. We then use GIS tools to construct site attributes, including the distance to employment centers, local infrastructure, and various amenities.

The first regression, shown in column (1) of Table 4, omits the interaction term in (16), regressing log land price on log FAR together with year fixed effects and site attribute variables, including distances to the CBD, the nearest major road, the nearest high school, and the nearest park. As in the regressions using the national dataset, log FAR has a positive coefficient. In addition, the land price falls with distance to the CBD and distance to the nearest park, a pattern that persists in the other regressions in Table 4.

To cope with potential endogeneity, we instrument log FAR with dummies for each of the 17 districts in Beijing. The idea is that district governments may have different infrastructure costs and different preferences for regulatory stringency, with both differences having no direct effect on land prices after controlling for site attributes. As seen in column (2) of the table, the two-stage least squares coefficient of log FAR is still positive and highly significant. Although the instruments pass the over-identifying test, the first stage F statistic (equal to 3.43) suggests a potential problem of instrument weakness.

In columns (3) and (4), we interact log FAR with the distance to Tiananmen in both the OLS and 2SLS estimations. Tiananmen is at the center of a cluster of low-density historical sites and government complexes. The Forbidden City, Tiananmen Square, the Great Hall of the People, and Zhongnanhai (headquarters for the Communist Party and the State Council) are all within a mile of Tiananmen. Thus, we suspect that the stringency of FAR limits is highest in the areas surrounding Tiananmen and declines moving away from it. Our regression analysis confirms this expectation. In particular, with negative estimated interaction coefficients, both the OLS and 2SLS results show that the coefficient of log FAR decreases with distance to Tiananmen, suggesting that FAR restrictions are less stringent farther away from this historical area.[22] Note that this conclusion also provides an internal check on the model's predictions. In particular, since FAR limits are known to be tight in

[22] For an attempt to estimate the cost of the building-height restrictions in Beijing, see Ding (2013).

Table 3: Regressions of *FAR* stringency on city characteristics

Variable	Residential Land $\hat{\theta}_c$ (1)	Residential Land $\hat{\theta}_c$ (2)	Commercial Land $\hat{\theta}_c$ (3)	Commercial Land $\hat{\theta}_c$ (4)
A. *FAR stringency and historical cultural heritage*				
Number of historical-cultural sites in city	-0.001 (0.002)	0.009 (0.005)*	0.001 (0.001)	-0.005 (0.009)
Log population size	0.071 (0.083)	-0.155 (0.128)	0.049 (0.066)	0.077 (0.185)
Log per capita city revenue	0.012 (0.082)	-0.090 (0.115)	-0.013 (0.078)	0.232 (0.220)
Log per capita public buses	0.067 (0.074)	-0.023 (0.132)	0.056 (0.059)	0.057 (0.195)
Log per capita paved road area	-0.077 (0.113)	-0.091 (0.179)	-0.069 (0.097)	-0.467 (0.276)
Constant	0.565 (0.484)	1.647 (0.792)**	0.605 (0.456)	-0.377 (1.430)
R^2	0.02	0.12	0.04	0.13
Number of observations	73	37	62	26
B. *FAR stringency and tourist status*				
Designated as tourist city after 2004	-0.067 (0.135)	0.073 (0.208)	-0.168 (0.109)	-0.859 (0.367)**
R^2	0.02	0.12	0.04	0.13
C. *FAR stringency and industry structure*				
Share of second sector in city's GDP in 2005	0.001 (0.004)	-0.013 (0.007)*	-0.003 (0.003)	0.027 (0.012)**
R^2	0.02	0.12	0.04	0.13

Standard errors are in parenthesis. Regressions in panels B and C include a constrant and the same set of controls as in panel A. Sample sizes in panels B and C are the same as in panel A. All control variables are in 2005 values. ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$.

Data source for historical-cultural sites: http://www.bjww.gov.cn/wbsj/zdwbdw.htm.
Data source for designated tourist cities: http://www.chinacity.org.cn/csph/csph/49786.html
Share of second sector in city's GDP is from the 2006 edition of the *China Urban Statistical Yearbook.*

Table 4: Regressions of land price on FAR: Beijing subsample

	Dependent Variable: Log unit land price			
	(1)	(2)	(3)	(4)
	OLS	2SLS	OLS	2SLS
Log FAR	0.647***	0.984***	3.800***	3.076***
	(0.151)	(0.135)	(0.981)	(1.108)
Log FAR*Log distance to Tiananmen			-0.306***	-0.194*
			(0.093)	(0.101)
Log distance to CBD	-0.381***	-0.323***	-0.283**	-0.244**
	(0.102)	(0.116)	(0.103)	(0.114)
Log distance to nearest major road	0.017	0.021	0.011	0.019
	(0.040)	(0.033)	(0.038)	(0.030)
Log distance to nearest high school	-0.019	0.018	-0.003	0.038
	(0.033)	(0.038)	(0.035)	(0.035)
Log distance to nearest park	-0.319***	-0.292***	-0.246***	-0.238***
	(0.063)	(0.068)	(0.084)	(0.093)
Constant	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
First-stage F statistic		3.43		
Sargan over-id test p-value		0.388		0.084
Number of obs.	327	327	327	327

Standard errors (in parenthesis) are clustered by city district. ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$. Endogenous variable in Column (2): Log FAR. Instrumental variables in Column (2): 17 district dummies. Endogenous variables in Column (4): Log FAR and Log FAR*Log distance to Tiananmen. Instrumental variables in Column (4): 17 district dummies, Log distance to Tiananmen, and their interactions.

the Tiananmen area, while the results show that this area has the highest elasticity of land price with respect to FAR, the link between stringency and this elasticity is independently confirmed.[23]

6.2 Adjustment of FAR levels in Beijing

Complementing the analysis in section 5.7, this section provides a different perspective on the determinants of regulated FAR levels by exploring the factors that led to *adjustments* in FAR levels for existing properties in Beijing over the 1999-2006 period. At issue is whether FAR adjustments respond to market pressures, reflecting a degree of efficiency in urban plannning. The analysis below uses the Detailed Planning Dataset (DPD) created by the Beijing Institute of City Planning, the government agency in charge of urban planning in the city of Beijing. In contrast to the CIA data used above, which exists because every local government must release this information as it auctions the use right for a parcel, the DPD's information on FAR restrictions comes directly from the planning agency in the city of Beijing, having been tabulated regardless of whether or not its use right was transferred during our study period.[24]

In the empirical analysis below, we again study land parcels in residential and commercial uses and focus on those parcels that have the same land-use type in both the 1999 and 2006 plans. Our study sample includes 2,589 residential land parcels and 2,822 commercial land parcels. For residential land, the average planned FAR was 1.99 in 1999 and 2.23 in 2006; this ratio was adjusted upward for 35.9 percent of the parcels and adjusted downward for 10.1 percent of the parcels (see Table 5). For commercial land, the average planned FAR was 2.11 in 1999 and 2.36 in 2006; this ratio was adjusted upward for 34.3 percent of the parcels and adjusted downward for 21.4 percent of the parcels.

For each land parcel observed in both 1999 and 2006, the DPD data contain information on local amenities, such as the distance to the city center, to the closest hospital, and to the closest park. This information is available for 2006 only, but the amenities are unlikely to have changed during the 1999-2006 period. However, access to the subway system is

[23] Instead of using the instrumental variable approach, we also tried to control for unobserved site attributes using cluster dummies, as in the approach used above in Table 2. However, the sample size for clustered land parcels is very small: we can only identify 53 residential land parcels in 22 clusters in the Beijing area. The results similarly suggest that the FAR restrictions are less stringent further away from Tiananmen, but the estimates are imprecise because of the small sample size.

[24] In 1999, a detailed planning exercise was carried out for the Central Area of Beijing City, which consists of the districts of Dongcheng, Xicheng, Chongwen, Xuanwu, Haidian, Chaoyang, Fengtai, and Shijingshan. For each land parcel, the 1999 plan specifies its land-use type as well as development restrictions including building height, floor-area ratio, ratio of green space, and residential density. In 2006, there was another round of detailed planning in Beijing. For each land parcel, the same kind of information is available as in 1999. Our analysis here focuses on the Central Area of Beijing, as covered by both the 1999 and the 2006 plans. Changes in planned FARs between 1999 and 2006 are identified by spatially linking these two datasets. We overlay the centroids of land parcels in 1999 (the point file) with land parcels in 2006 (the polygon file) using ArcGIS. For each land parcel in 1999, its information in 2006 is obtained from the 2006 land parcel in which the 1999 centroid is located.

Table 5: *FAR* changes between 1999 and 2006

	Residential Land		Commercial Land	
	Mean	Std Dev	Mean	Std Dev
FAR in 1999	1.993	0.602	2.107	1.937
FAR in 2006	2.234	0.873	2.359	1.513
	Observations	%	Observations	%
FAR increased	930	35.9	968	34.3
FAR unchanged	1,398	54.0	1,250	44.3
FAR decreased	261	10.1	604	21.4
Total	2,589	100	2,822	100

Land parcels included in the left column were specified for "residential" uses for both 1999 and 2006 plans; land parcels included in the right column were specified for "commercial" uses for both 1999 and 2006 plans.

another important amenity, and because of dramatic expansion of the system in the early 2000s, access is likely to have changed over the period for a typical parcel. Fortunately, the DPD data contain the distance to the closest subway station in both 1999 and 2006.[25] We examine changes in regulated *FAR* in the city of Beijing in response to demand pressure, exploiting the variation created by the rapid expansion of the city's subway system.[26]

The estimating equation is

$$\Delta \ln FAR_{jd} = \rho_d + \phi \Delta D_{jd} + Z_{jd}\gamma + \upsilon_{jd}, \tag{20}$$

where $\Delta \ln FAR_{jd}$ is the change in regulated *FAR* for land parcel j in district d of Beijing, ρ_d is a district-specific intercept, ΔD_{jd} represents the change in distance to the closest subway station (as new subway lines are constructed), Z_{jd} is a vector of time-invariant locational characteristics, and υ_{jd} is the error term. We expect improved subway access to lead to an upward adjustment of *FAR*, so that $\phi < 0$.

Table 6 presents the regression results, starting with a simple specification where the

[25] A map of areas covered by the 2006 planning, which is available on request, reveals a few facts worth noting: (1) Tiananmen (at the center of the map) and its surrounding areas have very low *FAR*s, consistent with the preservation of historical sites, as noted above; (2) The central business district and the financial district have mostly commercial land with very high *FAR*s; (3) *FAR*s are generally higher in the northwest than in the south.

[26] The construction of the Beijing subway system started in the 1960s, and the system evolved slowly during the next three decades. By 1999, the system consisted of only two lines: line 1 and the ring line. In 2001, Beijing was selected as the host of the 2008 Olympic Games, which spurred a massive construction of infrastructure in the city, including several new subway lines. By the end of 2003, line 13, line 5, and the Batong line were put into service. By the summer of 2008, line 10, line 8, and the Airport line were also in operation. These dramatic changes altered the local conditions for many land parcels in the city. We take advantage of these spatially varying shocks, investigating their effects on regulated *FAR*s. For related work on the effect of subway proximity on Beijing property values, see Li et al. (2015), Wang (2015) and Zheng and Kahn (2008, 2013).

Table 6: Regression relating *FAR* changes to their determinants, 1999-2006

Dependent Variable: Changes in log FAR between 1999 and 2006				
	Residential Land		Commercial Land	
	(1)	(2)	(3)	(4)
Change in log distance to nearest subway station	-0.0186** (0.0061)	-0.0166** (0.0064)	-0.0164 (0.0101)	-0.0249 (0.0139)
Log FAR in 1999	-0.3307*** (0.0311)	-0.376*** (0.041)	-0.2309*** (0.0523)	-0.2603*** (0.0482)
Log distance to nearest subway station in 1999		-0.0410** (0.0167)		-0.0958** (0.0306)
Log distance to Tiananmen		0.1854*** (0.0372)		0.1840*** (0.0513)
Log distance to 2nd Ring Road		-0.0362** (0.0131)		-0.0487** (0.0164)
Log distance to nearest highway		0.0366 (0.0223)		0.0493 (0.0267)
Log distance to nearest key middle school		0.0003 (0.0146)		0.0160 (0.0123)
Log distance to nearest hospital		0.0017 (0.0128)		0.0399** (0.0148)
Log distance to nearest park		0.0238** (0.0081)		0.0469*** (0.0070)
Constant	Yes	Yes	Yes	Yes
District dummies	No	Yes	No	Yes
Adjusted R^2	0.0886	0.1241	0.0830	0.1435
Number of obs.	2,588	2,588	2,772	2,772

Standard errors (in parenthesis) are clustered by city district. ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$. There are eight district dummies.

change in log FAR between 1999 and 2006 is related only to the change in log distance to the nearest subway station, controlling for the 1999 log FAR level (columns (1) and (3)). The residential ϕ coefficient is negative and significant, indicating that, as expected, a reduction in distance to the nearest subway station leads to an upward adjustment in FAR. The ϕ coefficient in the commercial regression is also negative and of the same order of magnitude, although it is less precisely estimated. In both regressions, an initially high FAR level moderates the upward adjustment over the 1999-2006 period.

In an alternative specification (columns (2) and (4)), we further control for distance to the nearest subway station in 1999, distance to Tiananmen, distance to the Second Ring Road, distance to the nearest highway, distance to the nearest key middle school, distance to the nearest hospital, distance to the nearest park (with all distances in logs), and city district dummies. Although these local characteristics were hardly changing between 1999 and 2006 (being measured by 2006 values), changes in development pressure could have been correlated with local conditions, as measured by these variables. For residential land, the key subway access coefficient hardly changes after all these controls are added, still being negative and statistically significant. For commercial land, the key coefficient is also negative but again statistically insignificant.

Among the control variables, the positive and significant coefficient on log distance to Tiananmen shows that land parcels closer to this site are less likely to have their FARs adjusted upward between 1999 and 2006, in line with previous results. Distance to the Second Ring Road and distance to the nearest park also have significant coefficients in both samples, with FAR more (less) likely to be adjusted upward closer to the Ring Road (closer to parks), patterns consistent with casual observation. Note also that, for a given reduction in log distance to a subway station, the upward FAR adjustment is smaller the worse is the initial level of subway access (log distance to a station in 1999).

Overall, the results in Table 6 suggest that FAR restrictions tend to be relaxed over time for residential land parcels in areas experiencing upward shifts in demand, as captured most prominently by improved subway access. This finding suggests that Beijing planners adjusted their regulations in response to market pressure, as economic efficiency would dictate. However, a cautionary note concerns potential endogeneity bias. It is possible that new subway stops are located in areas with unobservable characteristics that also favor increases in FAR, implying that the change in the distance to the nearest subway stop is negatively correlated with the regression error term. While this possibility means that the FAR coefficient may be somewhat downward biased, it is unlikely that any such bias fully accounts for the observed negative effect.

7 Conclusion

This paper has developed a new approach for measuring the stringency of a major form of land-use regulation, building-height restrictions, and it has applied the method to an extraordinary dataset of land-lease transactions from China. Our theory shows that the elasticity of land price with respect to the FAR limit is a measure of the regulation's stringency (the extent to which FAR is kept below the free-market level). Using a national sample, estimation that allows this elasticity to be city-specific shows substantial variation in the stringency of FAR regulation across Chinese cities, and additional evidence suggests that stringency depends on certain city characteristics in a predictable fashion. Single-city estimation for the large Beijing subsample, where site characteristics can be added to the regression, indicates that the stringency of FAR regulation varies with certain site characteristics, again in a predictable way (being high near the Tiananmen historical sites). Additional results for Beijing relying on a different data set show that FAR limits for previously developed sites are appropriately adjusted upward in response to demand pressure introduced by new subway stations.

Our method for measuring the stringency of land-use regulation reflects the intuitive notion that relaxing a very tight regulation should raise the price of land by more than relaxing a loose regulation. This method could be applied to height regulations in countries other than China (assuming suitable data is available), and it could also be applied to any regulation that, like FAR, involves a continuous index. Such regulations would include other types of density regulations or building set-back rules, for example. Like the regulatory tax of Glaeser et al. (2005), our method invites wide application.

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Appendix Table A-1: City-specific coefficients for residential land

Estimated using the full sample		Estimated using the matched sample
1. Qinhuangdao -0.011	41. Other cities 0.812	1. Foshan -0.557
2. Xi'an -0.011	42. Fuzhou 0.815	2. Shanghai -0.474
3. Erdos 0.027	43. Dongguan 0.827	3. Qinhuangdao -0.462
4. Kaifeng 0.103	44. Wuxi 0.841	4. Tianjin -0.269
5. Yingkou 0.120	45. Ningbo 0.843	5. Yingkou 0.000
6. Zhongshan 0.234	46. Guiyang 0.856	6. Kunming 0.003
7. Quanzhou 0.268	47. Changzhou 0.857	7. Anshan 0.006
8. Anshan 0.296	48. Langfang 0.867	8. Urumqi 0.098
9. Shanghai 0.316	49. Changchun 0.893	9. Nantong 0.112
10. Foshan 0.323	50. Shenzhen 0.894	10. Fushun 0.129
11. Ezhou 0.382	51. Weihai 0.904	11. Linyi 0.136
12. Yangzhou 0.425	52. Zhengzhou 0.908	12. Ezhou 0.180
13. Tangshan 0.428	53. Taizhou 0.913	13. Suzhou 0.205
14. Zibo 0.496	54. Fushun 0.928	14. Zhongshan 0.214
15. Linyi 0.510	55. Dalian 0.941	15. Chengdu 0.222
16. Guangzhou 0.538	56. Shenyang 0.945	16. Wuhan 0.242
17. Chengdu 0.547	57. Huaian 0.960	17. Weifang 0.246
18. Weifang 0.549	58. Nanchang 0.963	18. Ningbo 0.288
19. Suqian 0.564	59. Changsha 0.964	19. Yancheng 0.317
20. Suzhou 0.573	60. Xiamen 0.972	20. Hangzhou 0.321
21. Ji'nan 0.637	61. Daqing 1.005	21. Tangshan 0.327
22. Urumqi 0.659	62. Zhenjiang 1.026	22. Jiaxing 0.330
23. Lianyungang 0.662	63. Xuzhou 1.043	23. Other cities 0.333
24. Jilin 0.672	64. Harbin 1.084	24. Changsha 0.368
25. Tianjin 0.687	65. Jiaxing 1.085	25. Langfang 0.457
26. Huzhou 0.688	66. Nanchong 1.086	26. Lianyungang 0.466
27. Hohhot 0.702	67. Mianyang 1.114	27. Erdos 0.482
28. Huizhou 0.717	68. Changde 1.137	28. Qingdao 0.486
29. Beijing 0.724	69. Yancheng 1.242	29. Ji'nan 0.493
30. Jinzhou 0.735	70. Nanning 1.289	30. Quanzhou 0.506
31. Yantai 0.741	71. Kunming 1.318	31. Chongqing 0.547
32. Chongqing 0.744	72. Jiujiang 1.453	32. Dalian 0.554
33. Taiyuan 0.751	73. Nantong 1.554	33. Yantai 0.565
34. Luoyang 0.765		34. Huizhou 0.607
35. Hefei 0.768		35. Shenyang 0.756
36. Nanjing 0.775		36. Luzhou 0.852
37. Shaoxing 0.775		37. Harbin 0.863
38. Wuhan 0.788		38. Zhengzhou 0.978
39. Qingdao 0.799		
40. Hangzhou 0.802		

City-specific coefficients in the left columns are from the estimation of equation (15) using the whole sample; they correspond to the summary in panel B of Table 2. City-specific coefficients in the right column are from the estimation of the cluster version of (15) using the matched sample; they correspond to the summary in panel D of Table 2.

Appendix Table A-2: *FAR* stringency and labor demand shocks

	Residential Log Land Price (1)	Residential Log Land Price (2)	Commercial Log Land Price (3)	Commercial Log Land Price (4)
Log FAR	0.680***	0.749***	0.545***	0.559***
	(0.042)	(0.033)	(0.030)	(0.020)
Log FAR*Bartick Index 1	1.261*		0.342	
	(0.650)		(0.386)	
Log FAR*Bartick Index 2		-0.235		2.476**
		(2.004)		(1.025)
Constant	6.850***	6.853***	7.043***	7.041***
	(0.024)	(0.024)	(0.015)	(0.015)
City-district by year fixed effects	Yes	Yes	Yes	Yes
R^2	0.68	0.68	0.64	0.64
Number of observations	28,616	28,616	24,175	24,175

Standard errors are in parenthesis. ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$.

Bartik Index 1 for city i in year t: $BI_{it}^1 = \sum_{j=1}^{J} s_{jit-1}g_{jt}$, where g_{jt} is the employment growth rate of industry j in year t in all cities other than city i and s_{jit-1} the employment share of industry j in city i in year $t-1$.

Bartik Index 2 for city i in year t: $BI_{it}^2 = \sum_{j=1}^{J} s_{jit-1}(g_{jt} - g_t)$, where g_{jt} is the employment growth rate of industry j in year t in all cities other than city i, g_t the overall employment growth rate in year t in all cities, and s_{jit-1} the employment share of industry j in city i in year $t-1$.

Data for calculating the Bartik indexes are from the 2004-2012 editions of the *China Urban Statistical Yearbook.*